Iterative Directional Ray-Based Iris Segmentation for Challenging Periocular Images*

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Abstract. The face region immediately surrounding one, or both, eyes is called the periocular region. This paper presents an iris segmentation algorithm for challenging periocular images based on a novel iterative ray detection segmentation scheme. Our goal is to convey some of the difficulties in extracting the iris structure in images of the eye characterized by variations in illumination, eye-lid and eye-lash occlusion, de-focus blur, motion blur, and low resolution. Experiments on the Face and Ocular Challenge Series (FOCS) database from the U.S. National Institute of Standards and Technology (NIST) emphasize the pros and cons of the proposed segmentation algorithm.

Keywords: Iris segmentation, ray detection, periocular images.

1 Introduction

Iris recognition is generally considered to be the most reliable biometric identification method. But, it most often requires a compliant subject and an ideal iris image. Non-ideal images are quite challenging, especially for segmenting and extracting the iris region. Iris segmentation for biometrics refers to the process of automatically detecting the pupillary (inner) and limbus (outer) boundaries of an iris in a given image. Here we apply iris segmentation within the periocular region of the face. This process helps in extracting features from the discriminative texture of the iris for personnel identification/verification, while excluding the surrounding periocular regions. Several existing iris segmentation approaches for challenging images, along with evaluations, can be found in [3,5,6].

This paper presents an iris segmentation technique for non-ideal periocular images that is based on a novel directional ray detection segmentation scheme.

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The method employs calculus of variations and directional gradients to better approximate the boundaries of the pupillary and limbus boundaries of the iris. Variational segmentation methods are known to be robust in the presence of noise [1,11] and can be combined with shape-fitting schemes when some information about the object shape is known a priori. Quite commonly, circle-fitting is used to approximate the boundaries of the iris, but this assumption may not necessarily hold for non-circular boundaries or off-axis iris data. For computational purposes, our technique uses directional gradients and circle-fitting schemes, but other shapes can also be easily considered. This technique extends the work by Ryan et al. [9], who approached the iris segmentation problem by adapting the Starburst algorithm to locate pupillary and limbus feature pixels used to fit a pair of ellipses. The Starburst algorithm was introduced by Li, et al. [7], for the purpose of eye tracking.

In this paper, experiments are performed on a challenging periocular database to show the robustness of the proposed segmentation method over other classic segmentation methods, such as Masek's Method [8] and Daugman's Integro-Differential Operator method [2]. The paper is organized as follows. In Section 2, we briefly introduce a periocular dataset representative of the challenging data considered in our tests. In Section 3, we touch upon the pre-processing procedures used to improve the accuracy of iris segmentation in the presence of challenging data. In Section 4, iterative directional ray detection with curve fitting is proposed. Section 5 describes the experimental results obtained with directional ray detection and conclusions are presented in Section 6.

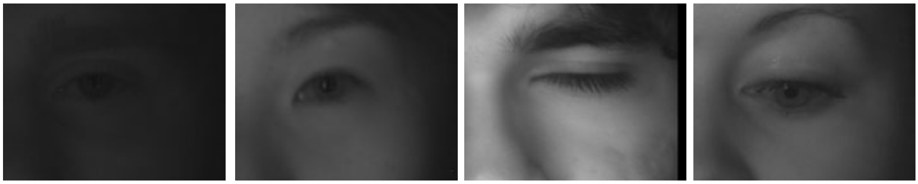
2 Face and Ocular Challenge Series (FOCS) Dataset

To obtain accurate iris recognition from periocular images, the iris region has to be segmented successfully. Our test database is from the National Institute of Standards and Technology (NIST) and is called the Face and Ocular Challenge Series database[1]. Performing iris segmentation on this database can be very challenging (see Fig. 1), due to the fact that the FOCS database was collected from subjects walking through a portal in an unconstrained environment [6]. Some of the challenges observed in the images include: poor illumination, out-of-focus blur, specular reflections, partially or completely occluded iris, off-angled iris, small size of the iris region compared to the size of the image, smudged iris boundaries, and sensor noise.

3 Image Pre-processing

For suppressing the illumination variation in FOCS images and thus improving the quality of iris segmentation, the following pre-processing scheme was used: (i) illumination normalization, (ii) eye center detection, and (iii) inpainting.

[1] See `http://www.nist.gov/itl/iad/ig/focs.cfm`



(a) Poor illumination (b) Blur (c) Occlusion (d) Off-angle

Fig. 1. Periocular FOCS imagery exhibiting non-ideal attributes

3.1 Illumination Normalization

Illumination variation makes it challenging to accurately and reliably determine the location of the iris boundaries. In general, the image contrast is very low and the iris boundaries are somewhat obscured. To increase the contrast and highlight the intensity variation across the iris boundaries, illumination normalization was performed by using the *imadjust* command in MATLAB. This normalization helps make intensity variation of different images more uniform, improving the stability of the proposed segmentation algorithm. Sample images obtained of before and after illumination normalization are shown in Fig. 2.

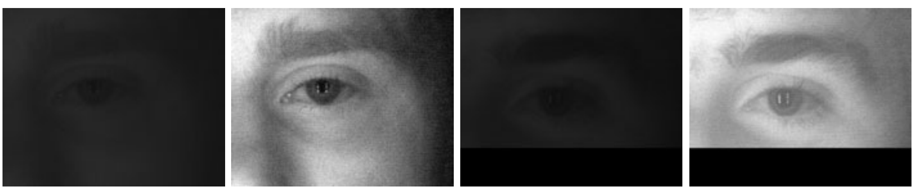


Fig. 2. Sample FOCS imagery before and after illumination normalization

3.2 Eye Center Detection

Reliably determining the location of the iris in the image is challenging due to noise and non-uniform illumination. We use an eye center detector method based on correlation filters. In this method, a specially designed correlation filter is applied to an ocular image, resulting in a peak at the location of the eye center. The correlation filter for the eye center detector was trained on 1,000 images, in which the eye centers were manually labeled. The correlation filter approach for detecting the eye centers, when applied on the full FOCS dataset, yielded a success rate of over 95%. Fig. 3(a) shows a typical image after eye center detection, where the eye center is shown with a small white dot. Fig. 3(b-c) show some of the rare cases where the eye center was not accurately determined. The accuracy of our iris segmentation method is crucially related to the correctness of eye center detection.

(a) Correct (b) Slightly offset (c) Completely offset

Fig. 3. Eye center detection for sample FOCS imagery (marked by white dots)

3.3 Inpainting

Specular reflections located within the iris region are additional factors affecting the success of iris segmentation. We use inpainting for alleviating this effect. In particular, an inpainting method [10] is applied to each image to compensate for the information loss due to over or under exposure. However, because of the non-uniform illumination distribution on some images, this step cannot completely remove specular reflections.

4 Iterative Directional Ray-Based Iris Segmentation

The proposed method involves multiple stages of a directional ray detection scheme, initialized at points radiating out from multiple positions around the eye region, to detect the pupil, iris, and eyelid boundaries. Specifically, it consists of three main sequential steps: (i) Identification of a circular pupil boundary by directional ray detection, key point classification and Hough transform [4]; (ii) Identification of the limbic boundary by iterative directional ray detection; and (iii) Identification of the eyelid boundary by the directional ray detection applied at multiple points.

4.1 Directional Ray Detection

Directional ray detection aims to identify the local edge features of an image around a reference point (x_s, y_s) or a set of reference points $\mathcal{S}$ along selective directions. Assume that the reference point (x_s, y_s) is an interior point of a pre-processed image $\mathcal{I}(x, y)$. Let r be the searching radius and a finite set $\Theta = \{\theta_i\}_{i=1}^{M} \subset [0, 2\pi]$ be the selective searching direction set. Directional ray detection results in a set of key points (x_i, y_i) along Θ in a circular neighborhood of radius r around (x_s, y_s) maximizing,

$$(x_i, y_i) = argmax_{(x,y)\in\Gamma(x_s,y_s,\theta_i,L)} \left|\omega_H * \mathcal{I}(x, y)\right|, \qquad i = 1, \ldots, M, \qquad (1)$$

where $\Gamma(x_s, y_s, \theta_i, L)$ denotes the θ_i direction rays of length of L radiating from (x_s, y_s), and ω_H is a high-frequency filter for computing gradients along rays.

In the implementation, we use $\omega_H = [-1, 0, 1]$. Locations for which the gradient difference reaches an absolute maximum are then selected as key points.

The main advantages of directional ray detection are flexibility and computational efficiency. With our method, we can easily control the reference points, searching radius, and searching directions, while exploring local information instead of the entire image.

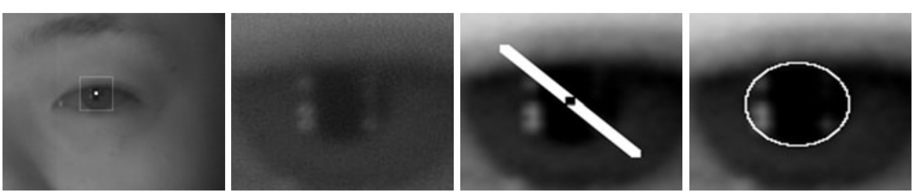
4.2 Pupil Segmentation

Assume that the eye center (x_c, y_c) of a pre-processed image $\mathcal{I}(x, y)$ is correctly located within the pupil, shown as a white dot in Fig. 4(a). Let $\mathcal{I}_p(x, y)$ denote a cropped region of size $2(r_p^{(l)} + r_p^{(u)})$ centered at (x_c, y_c), where $0 < r_p^{(l)} < r_p^{(u)}$ are pupil radius bounds determined experimentally from the dataset. A sample region $\mathcal{I}_p(x, y)$ containing a pupil is shown in Fig. 4(b). For computational efficiency, pupil segmentation is performed on $\mathcal{I}_p(x, y)$. Pupil segmentation is an iterative algorithm. Each iteration includes ray detection to extract structural key points, classification to eliminate noisy key points, and the Hough transform to estimate the circular pupil boundary.

In each iteration, key points of the pupil are efficiently extracted using Eq. (1), setting (x_c, y_c) as the reference point. For the FOCS dataset, we set

$$\Theta = \{\frac{\pi}{4} + \frac{i\pi}{M}\}_{i=1}^{\frac{M}{2}} \cup \{\frac{5\pi}{4} + \frac{i\pi}{M}\}_{i=1}^{\frac{M}{2}},$$

assuming M is an even number, to avoid the specular reflection in the horizontal direction as shown in Fig. 4(c). To remove outliers, we apply k-means intensity classification for grouping all the key points into two groups, pupillary edge points and non-pupillary edge points. The process depends on the fact that the intensity of pixels inside the pupil is lower than in other portions of the eye, such as the iris and eyelids. The Hough transform is then applied to selected pupillary edge points, the estimated pupil center (x_p, y_p), and the radius of the pupil r_p as shown in Fig. 4(d). We use (x_p, y_p) and r_p as inputs of the next iteration.



(a) $\mathcal{I}(x, y)$ (b) $\mathcal{I}_p(x, y)$ (c) Directional rays (d) Segmented pupil

Fig. 4. One iteration of Iterative Directional Ray Segmentation for the pupil

4.3 Iris Segmentation

Similarly to pupil segmentation, we determine key points along the irs based on our adaptive directional ray detection and apply the Hough transform to find the iris boundary. Let $\mathcal{I}_I(x,y)$ be a cropped image region of size $2(r_p^{(l)}+r_I^{(u)})$ centered at the estimated pupil center (x_p, y_p), where $r_I^{(u)}$ is a bound parameter of the iris radius determined experimentally from the data. In this step, directional ray detection in Eq. (1) is performed on $\mathcal{I}_I(x,y)$ with a set of reference points $\mathcal{S}_{\theta_i}$ along directions $\theta_i \in \Theta$ for $i = 1, \ldots, M$. Here, given $0 < \alpha < 1$ and $N_s > 0$, we have

$$\mathcal{S}_{\theta_i} = \{(x,y)|x = x_p + (1+\alpha)r_p \cos t; y = y_p + (1+\alpha)r_p \sin t,\ t \in \mathcal{T}_{\Theta_i}\}$$

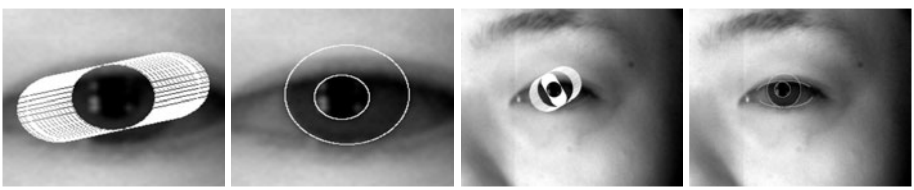
with

$$\mathcal{T}_{\Theta_i} = \{\theta_i - \frac{\pi}{2} + \frac{j\pi}{Ns}\}_{j=0}^{N_s}$$

and

$$\Theta = \{-\frac{\pi}{6} + \frac{i2\pi}{3M}\}_{i=1}^{\frac{M}{2}} \cup \{\frac{5\pi}{6} + +\frac{i2\pi}{3M}\}_{i=1}^{\frac{M}{2}}.$$

As shown in Fig. 5(a), the direction θ_i of test rays is close to the horizontal axis to avoid the upper and lower eyelid regions. After applying the Hough transform on the iris key points, we obtain the limbus boundary, as shown in Fig. 5(b).



(a) Rays ($\theta_i = \frac{\pi}{12}$) (b) Segmented iris (c) Eyelids detection (d) Visible iris

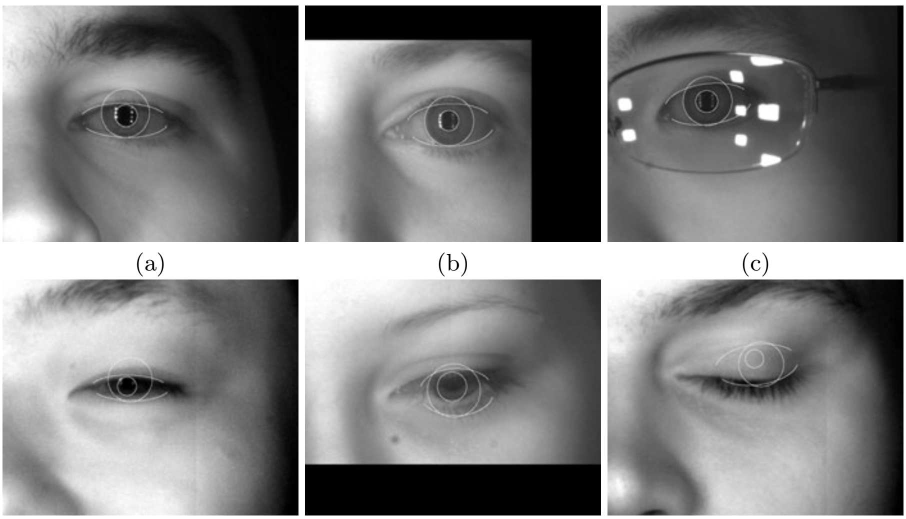
Fig. 5. Iterative directional ray detection results for iris and eyelids

4.4 Eyelid Boundary Detection

Detecting the eyelid boundaries is an important step in the accurate segmentation of the visible iris region as well as for the determination of iris quality metrics. The eyelid boundaries extraction is accomplish by a two-step directional ray detection approach from multiple starting points. As shown in Fig. 5(c), we set the rays to radiate from the pixels outside the boundaries of the pupil and iris regions along certain directions. Two groups of rays are chosen roughly along the vertical and horizontal directions. Eq. (1) is applied to these two groups of rays resulting in edge points along the eyelid. A least squares curve fitting model is then applied, resulting in a first fitting estimation to the eyelid boundary. To improve accuracy of the estimation in the previous step, we apply directional ray detection in the interior regions of the estimated eyelids. A new set of key points is obtained. The least squares fitting model is then applied again, resulting in an improved estimation of eyelid boundary, as illustrated in Fig. 5(d).

5 Experimental Evaluation

To evaluate our approach, experiments were performed on a sample subset of 404 images chosen from the full FOCS dataset, where comparisons are made with Masek's [8] and Daugman's [2] methods. The sample dataset was assured to be representative of the full FOCS database in terms of the challenges possessed. We also applied the proposed method to 3481 FOCS challenging periocular images. Fig. 6(a-c) provides examples of where the proposed method provided good iris segmentation, while Fig. 6 (d-f) shows images where the segmentation failed.



(a) (b) (c) (d) (e) (f)

Fig. 6. Successful (top) and unsuccessful (bottom) segmentation examples obtained by Directional Ray Detection

The overall accuracy of the iris segmentation technique on the FOCS dataset was measured as follows:

$$\text{Segmentation Accuracy} = \frac{\text{Number of successfully segmented images}}{\text{Total number of images}} \cdot 100\%,$$

where successfully segmented images means that the segmented iris is exactly the visible iris or is extremely close to it with about $\pm 2\%$ tolerance error in terms of area. A comparison of the proposed method with Masek's segmentation [8] and Daugman's Integro-Differential Operator method (IDO) [2] is shown in Table 1. Although Masek's segmentation and the Integro-Differential Operator were observed to use less computation time, the quality of segmented output is not acceptable (see Table 1). The new algorithm provides better performance at the expense of higher computational cost. The average computational time

Table 1. Segmentation accuracy of the Masek, IDO, and our proposed method

Methods	Total number of images	Number of successfully segmented images	Segmentation accuracy
Masek[8]	404	210	51.98%
IDOperator[2]	404	207	51.23%
Proposed method	404	343	**83.9%**

per image of the proposed method is about 15.5 seconds on a PC with a core i5vpro CPU.

Based on the comparisons in Table 1, promising performance of the proposed method in terms of accuracy is observed. Furthermore, we evaluate the ray-based method on a larger dataset, containing 3841 FOCS periocular images. As illustrated in Table 2, the segmentation accuracy is 84.4%, which highlights the overall performance and robustness of the proposed method in processing challenging periocular images.

Table 2. Segmentation accuracy of the proposed method on 3481 challenging FOCS periocular images

	Total number of images	Number of successfully segmented images	Segmentation accuracy
Proposed method	3481	2884	**84.4%**

6 Final Remarks

Iris recognition of low-quality images is a challenging task. A great deal of research is currently being conducted towards improving the recognition performance of irides under unconstrained conditions. Iris segmentation of challenging images is one of the crucial and important components of this work, whose accuracy can dramatically influence biometric recognition results. The main contributions of our paper are: (1) we provide a new segmentation method which is shown to be robust in processing low-quality periocular imagery, and (2) test our method a challenging dataset with poorly controlled iris image acquisition.

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